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From pit to electronic trading: Impact on price volatility of U.S. Treasury futures

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ABSTRACT

This paper investigates the dynamics of price volatility and trading volume of 10-year U.S. Treasury note futures within the context of transition from pit to electronic trading. The analysis is conducted over four discernible phases of futures trading evolution: the pit-only phase, the leap to electronic trading, and the electronic trading dominant phase, which is divided further into two periods, the before and after the financial crisis of 2007/2009. Generalized autoregressive conditional heteroskedasticity with in-mean conditional variance and generalized error distribution parameterization (GARCH-M-GED) tests are conducted to examine the conditional volatility of total returns index as a function of trading volume. The empirical results show a consistently negative relationship between the trading volume and price volatility for all four analyzed phases. They also show decreasing leptokurtosis (except for the direct effects of the recent crisis), continuously high persistency in volatility, as well as a weakening impact of unexpected ARCH-type shocks during the most recent analyzed period. Overall, the shift to electronic trading entails a substantial increase in trading volume, but not in price volatility of Treasury futures.

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1. Introduction

Financial markets for trading futures on U.S. Treasury notes and bonds have undergone major institutional evolution since they were first introduced in the 1970s. One of the critical innovations has been the transition from the open-outcry pit trading to electronic trading. This major institutional change affected the price discovery process in several critical ways. First, it allowed for extending the trading time from the U.S. business hours to a round-the-clock 24-hour period. Second, the process of matching buyers and sellers moved away from the hand signals used by pit traders to lightning-fast electronic trade matching algorithms. Besides enhancing the speed and the efficiency of price discovery, the shift to electronic trading is credited with reduced transaction costs. All of this occurred during a long, secular bull market for U.S. Treasuries. More recently, the global financial crisis of 2007/2009 brought about further institutional changes to futures markets, namely new regulatory legislation in the form of the Dodd–Frank Act. In addition, the crisis induced a considerably increased buying activity of long-term U.S. Treasury securities by the Federal Reserve.

Recognizing these changes, this study aims to examine the impact of the transition from pit to electronic trading on the nature and patterns of price volatility and trading volume of 10-year Treasury note (T-note) futures. The main investigative question is whether price volatility was affected by the massive increase in trading volume that has occurred with the introduction of the electronic trading. This study contributes

new dimensions to the literature on futures markets by focusing on the dynamics of price volatility and trading volume in the context of major institutional change. The general hypothesis is that the transition from pit to electronic trading has improved market liquidity of T-note futures due to higher trading volume, while price volatility has remained relatively unaffected.

For the purpose of assessing the impact of the transition, the trading pattern of 10-year T-note futures is analyzed over four discernible phases. Phase I includes the pit-only trading. It captures the period from the beginning of 1982 when 10-year T-note futures were introduced by the Chicago Board of Trade (CBOT) to August 28, 2000 when full round-the-clock electronic was launched.¹ Phase II corresponds with the fast-track leap to electronic trading, i.e. August 28, 2000 to September 12, 2003 when a well-defined full electronic trading dominance was reached (defined as a persistent plus-85% share of 10-year T-note futures electronic in total trading). Phases III and IV are characterized by the dominance of electronic trading, with the open-outcry pit trading playing only a marginal role. These last two phases are separated by the onset of the financial crisis.

The empirical tests are based on daily data for 10-year Treasury note futures made available by the CME Group. The sample period begins in January 1982 and runs through the end of 2011. The data set contains information for every contract stub (maturity), every trading day, for open, high, low, and settlement prices, trading volumes in the regular

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¹ Notably, the after-hours electronic trading was in place prior to August 2000, but its share in the overall market activity was minor.

pit sessions and on the electronic platform, and open interest. This data set allows deeper understanding of price volatility beyond the typical standard deviation of price returns to investigate what was happening simultaneously with intra-day high-to-low price differences and trading volumes. Under normal distribution assumption, there would be a stable relationship between the standard deviation of price returns and the intra-day high-to-low percentage price difference. However, in this paper conditional volatility characteristics are examined by employing generalized autoregressive conditional heteroskedasticity GARCH(p,q) model augmented with the general error distribution (GED) parameterization that accounts for leptokurtosis, i.e. tail risks in the data distribution.

A continuous total return index for the 10-year T-note futures has been constructed by the CME Group and made available for this study. It serves as a basis to ascertain futures price volatility. This data series essentially represents an excess return series above the interest one might earn from the futures margin account or deployment of the available capital given the embedded leverage in the structure of futures contracts. Notably, calendar rolls occur four times a year in Treasury futures, and market participants typically exit the current contract prior to the commencement of the delivery period. Depending on the level of short-term interest rates embedded in futures prices, there can be meaningful price gaps between the expiring contract and the next maturity date. Simply splicing price data as the nearby contract expires introduces volatility into the series and incorrectly handles price returns four times each year, with some of these cases being non-trivial for return analysis. Thus, the CME-constructed total return index gives a better picture of how market participants actually experience price movements in Treasury futures, compared with ignoring the price bumps involved in a calendar roll, as well as the more nuanced trading that occurs during the delivery period in the last month of the nearby contract.

Section 2 provides a perspective on the transition from pit to electronic trading along with a brief overview of the pertinent literature. Section 3 introduces the four phases of evolution of futures trading and describes the methodology for verifying break points between them. The conditional price volatility analysis of the 10-year T-note futures returns is examined and discussed in Section 4. Section 5 summarizes the main arguments and findings.

2. Perspective on transition from pit to electronic trading and literature overview

The literature examining institutional changes in futures markets has been extensive. The transition from the open-outcry pit trading to electronic trading has been examined from various institutional perspectives. The literature on this subject dates back to 1992, shortly after the Chicago Mercantile Exchange created Globex, which was initially used for after-hours trading exclusively and applied only to certain selected and specific futures products. Virtually all major futures exchanges experimented with electronic trading platforms during the 1990s, including the CBOT which operated the 10-year Treasury note futures product.

It should be emphasized that the decision to introduce electronic trading was not made without significant controversy. The history of the decision process is laid out in detail by Melamed (2009). Futures exchanges, including CME Group, are now organized as public companies with openly traded shares of stock, but in the 1990s both the CME and the CBOT were mutual organizations owned by their members. And their members, most of whom earned their livings from floor trading, at least initially were not all in favor of the move to electronic trading on a 24-hour basis in direct competition to floor trading. In addition, the investment in an electronic trading platform and the software development of trade matching engines was expensive, not easy to accomplish, and embodied considerable operational risk. Indeed, the CBOT used a number of different electronic platforms for its 10-year

T-note futures product during the transition period from pit to electronic trading.

Much of the discussion in the academic literature has been focused on trading various financial futures in three distinctive trading systems: the floor-dominant, the hybrid floor/automated, and the automated dominant systems. Perhaps the most discernible functional distinctions between the floor-dominant versus automated dominant systems are that the first one is conducted only during specific daytime business hours and requires person-to-person interaction to match buyers and sellers while the second one runs almost 24 h (with a short break to reset the day) and buyers and sellers are matched with electronic trading algorithms that operate in a lightning fast manner. Both of these distinct differences have had their impacts on futures markets.

Round-the-clock trading does not just open up futures market for “after-hours” trading, it reaffirms the global nature of markets and better aligns futures with cash or physicals markets. There was nothing stopping Asians and Europeans from placing orders before the open of U.S. pit trading in Treasury futures, but futures trades could not be executed until the bell rang for trading to commence. For those outside the U.S. time zones, if one wanted to trade the market actively, one had to trade during one's night-time hours. Initially, in the 1990s, electronic platforms first handled only after hours trading, and were later extended to 24-hour trading overlapping the pit trading sessions.

The lightning-fast trade matching algorithms expanded the ability of certain market participants to trade more actively. Again, active trading has always been a feature of organized markets, but technology has altered what is possible. In the pit era, active traders wore the moniker of “day traders”, while in the electronic era we have “high-frequency traders”. It is a natural process of the evolution of how organized markets provide liquidity for all participants.

Much of the analytical literature was written during the transition from the open outcry to electronic trading. This literature discusses key characteristics of both trading platforms while attempting – with varying degrees of success – to identify the potential key *advantages* of the electronic trading over its floor-based predecessor. Ates and Wang (2005) discuss such characteristics as faster speed, accuracy in transactions processing, lower operating costs, open access to the limit order book, and anonymity of trader identification. These “technical” advantages allowed some authors to point toward the general conclusion that automated trading would likely contribute to greater market liquidity and to a faster, more efficient price discovery process (Martens, 1998).

The empirical literature comparing various features of electronic and the open-outcry pit system has strongly emphasized the benefit of lower transaction costs brought forth by the automated markets, due to a much faster order execution in these order-driven markets. A number of studies including Venkataraman (2001), Coppejans, Domowitz, and Madhavan (2006), as well as Tse and Bandyopadhyay (2006) indicate that cost savings from moving to automated from the open-outcry markets can be passed onto market participants in the form of lower fixed transaction costs. In addition, Gutierrez and Tse (2009) argue that the electronic trading systems entail lower inventory control costs.

The open access to limit order books and the anonymity of trader identification in electronic markets are related to the major difference in information extraction in the open-outcry versus electronic markets. In floor-based trading, the pit traders and floor brokers know and select each other, while they remain anonymous in a global electronic framework. Following this notion, Theissen (2003) makes an interesting observation that informed traders prefer to transact in an automated market, because they have incentives to hide and remain anonymous. Moreover, limit order traders in automated markets take advantage of volatility information. Foucault, Moinas, and Theissen (2007) examine whether limit order traders formulate information about future volatility on the basis of the bid–ask spread. They find that the average quoted spreads are smaller when limit order traders' identifiers are concealed, as the lower spreads may reduce their expectations about future volatility.

Other widely-debated advantages of electronic markets focus on the price discovery and the transactions matching process. Among others, Ates and Wang (2005) indicate that the algorithm matching protocol in electronic markets allows for a closer alignment of exchange counterparties. As a result, the faster transactions' execution ultimately lowers the execution risk and the order processing costs. In a different vein, Brandt, Kavajecz, and Underwood (2007) argue that price discovery in both Treasury futures and cash markets is driven mainly by a number of 'environmental' factors such as the trader type, financing rates and liquidity.

The literature also discusses the possibility, however, of several potential drawbacks of electronic trading in relation to the open-outcry trading pit. The most widely debated presumed disadvantage of electronic markets is a possibly heightened volatility and greater uncertainty of returns (Aitken, Almeida, Harris, de, & McNish, 2007; Aitken, Frino, Hill, & Jarnecic, 2004; Tse & Zabolina, 2001). An early study by Martens (1998) argues that automated markets result in larger trading volumes and in potentially higher volatility, particularly at stressful market periods. This stems from a more open and faster access by a broad spectrum of global investors in various types of financial futures (Gutierrez & Tse, 2009). Of course, the cause that generates the stressful period is the ultimate source of the volatility, and larger trading volumes and more liquid markets may well have allowed for considerably more rapid adjustment to the shock that caused the market volatility in the first place.

While the literature written during the transition period from pit to electronic trading raised some interesting points and contained a number of key insights, much of it was merely hypothetical because the transition was still in progress. This study, through its examination of the evolution of futures trading benefits from a longer data period that allows to analyze trading volume and price volatility under both floor-based and electronic trading platforms.

3. Evolution of Treasury futures trading: four discernible phases

The data for this research has been provided by the CME Group as part of their "End of Day" data packages for their futures products. The data available for 10-year T-note futures contains daily data from the regular pit trading session from the beginning of the data set in 1982 through the end of 2011. The data includes the settlement price, high price during the session, low price during the session, and trading volume. For the 24-hour electronic sessions, the data set commences at the end of August 2000, with the electronic sessions overlapping the regular hours of the pit sessions. As in the case for the pit sessions, the data for the electronic platform includes the settlement price and trading volume. The settlement procedure is such that the daily settlement prices are identical for both pit and electronic trading. The data set does not include prices for the after-hours electronic sessions that were introduced by the CBOT for Treasury futures in 1994. Trading information is not separated into pit and electronic session data until August 2000. To better mimic the price returns actually experienced by futures market participants, a long-only total return series has been created. This series handles the contract roll at the end of the month prior to the expiration of the contract and before the start of the delivery notice period.

In this paper, the evolution of the 10-year Treasury note futures market is divided into four distinct phases. These sub-periods have been determined through Chow Breakpoint tests in the data series reflecting the share of electronically traded 10-year T-note futures volume as a percent of total trading volume as shown in Fig. 1. The four phases are:

1. *Pit-only phase.* The period of exclusive CBOT floor-based trading runs from the inception of the 10-year Treasury note futures trading on May 3, 1982 to August 27, 2000 when the 10-year T-note futures were placed on a 24-hour electronic trading platform by the CBOT.

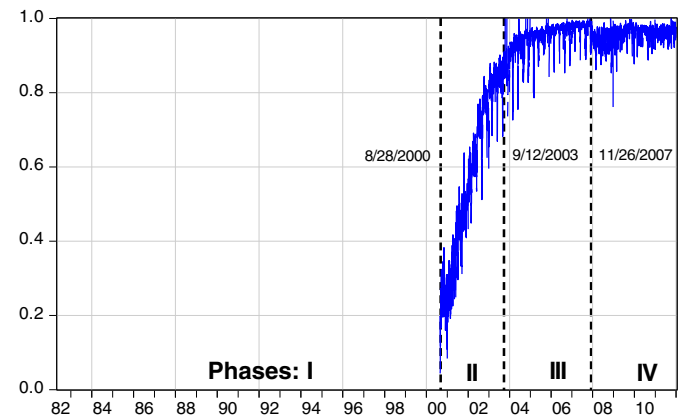


Fig. 1. Share of 10-year T-note Futures trading volume on electronic (Globex) platform as a percent of total trading volume. May 3, 1982–December 31, 2011 sample period. Source: Author's own estimation based on CME Group data.

2. *Leap to electronic trading.* During this hybrid, transitional phase, electronic trading gained traction at a rapid pace. Active trading in both the pit session and on the electronic trading system co-existed from August 28, 2000 (4% share trading on the electronic platform) to September 11, 2003 (share of electronic trading reaching plus-85% on a persistent basis).
3. *Electronic dominant trading.* This phase epitomized well-established electronic trading system that ran from September 12, 2003 to November 26, 2007. The end-point coincides with a major, temporary disruption in the electronic share from 99% to 90% that was induced by the U.S. subprime mortgage debacle spreading through the financial system. In an important note, during this period CME and CBOT merged to form the CME Group in October 2006. The electronic platform was eventually switched to CME's Globex during 2007.
4. *Electronic dominant with limited pit trading.* This period coincides with the global financial crisis that persisted from November 27, 2007 through December 30, 2011 (the end of our sample period). While electronic trading remained dominant, there was a limited revival of pit trading that stemmed from the elevated systemic risk crisis. The resurgence of traditional trading, especially in a crisis period, was in part potentially related to the benefits of human intermediation on a trading floor over the lack of it in the electronic only trading².

The cutoff date of September 12, 2003, i.e. between the end of Phase II and the starting point of Phase III has been determined with the Chow Breakpoint Test conducted for the percentage share of electronic trading with the linear time trend for the entire sample period (see Table 1). The November 26, 2007 breakpoint between Phase III and Phase IV has been also identified with the Chow test for the sample period between September 12, 2003 and December 31, 2011. Its timing roughly coincides with the recognition that the recent financial crisis was no longer confined merely to the subprime mortgage demise but it was reverberating rapidly across global financial markets³.

One note here is that there are down spikes in the share of electronic volume every three months. These down spikes in electronic volume and increased pit activity are associated with roll periods. In hindsight, traders handle the calendar roll differently than normal trading activity, and when traders and investors are rolling from one maturity that is expiring into the next, there is an increase in pit activity even in the

² The benefits of human intermediation, i.e. the floor trading, have been discussed in the earlier literature by Venkataraman (2001), among others. Chief among them is verification of data accuracy, including pricing.

³ For a comprehensive examination of stages of proliferation of the recent global financial crisis see Orlowski (2008).

Table 1
Chow Breakpoint Test summary statistics.

Breakpoints:	F-statistics	Log likelihood ratio
September 12, 2003	15,507	7065
November 26, 2007	397	675

Source: Author's own estimation based on CME Group data.

electronic era. In the 10-year T-note futures market, one has to signal the intent to deliver the physical securities at the start of the last month of the contract. Thus, for example, the March contract would end normal trading in February and start its delivery period during the first days of March, and similarly, for the June, September, and December contracts, since the Treasury futures trade on a quarterly contract cycle. The roll period into the new to be “nearby” contract occurs toward the end of the month before contract maturity or expiration, and it is then that the pit trading retains some role in the price discovery process even in the electronic era.

Some discernible changes in trading volumes and open interest that have accompanied the move to the electronic era are shown in Table 2. The open interest and trading volume data show sharp contrasts during the examined sample periods, reflecting a rapid institutional advancement of the 10-year T-note futures market. Notably, the average open interest in Phase IV (2008–2011) is 15 times higher than the pit trading era (1982–2000), while trading volumes are 18 times higher, for the same period averages. The average open interest during the first business 60-days increased from a “miniscule” 17 thousand during the pit-only phase, to close to 4 million during the most recent period. Another noteworthy observation is the considerably higher ratio of the average open interest during the last 60 business days to the overall open interest in Phase III (3.4 to 1.9 million) than in Phase IV (3.0 to 3.2 million), which reflects a somewhat weaker position of rolls during the most recent period. While the number of open interest, i.e. outstanding contracts held by investors at the end of each day, has increased considerably, their variability, or more specifically, the average daily dispersion from the mean as reflected by the coefficient of variation fell from 0.91 (or 91%) in Phase I to 0.24 in Phase II. It gradually increased to 0.27 in Phase III and 0.34 in Phase IV. It can be therefore argued that the introduction of electronic trading has dampened the overall variability of open interest, consistently with the initial intentions of the Globex platform architects (see Melamed (2009)). Similarly, the

average daily dispersion of daily trading volumes fell from 1.06 during the pit-only period to a sustainable 0.49 in Phases III and IV. Moreover, the proportion of trading volumes during the last 60 business days to the overall daily average volumes was overwhelmingly greater in Phase I (155/55 ratio), significantly larger in Phases II and III, but smaller in Phase IV (1015/1075 ratio), which further underpins stability gains in the examined Treasury futures market brought forth by the Globex trading.

While the volatility of daily returns in the 10-year T-note futures market appears fairly stable in terms of averages for each period, ranging from a high of 8.17% annualized standard deviation in Phase IV to a low of 6.12% in Phase III, this obscured many shorter time frames of much higher or lower volatility. Fig. 2 shows the rolling one-quarter (65 business days) annualized volatility. This time pattern underpins our claim that the shift to electronic trading of 10-year T-note futures has no discernible impact on their daily returns. As expected, their volatility has been recently elevated during the peak of the global financial crisis in the last quarter of 2008.

In short, there was a great deal of market action during the period under study, as trading evolved from pit to electronic sessions.

Further insights to the impact of trading on electronic platforms on liquidity and volatility of the 10-year T-note futures market can be detected from the analysis of bivariate reactions between the percentage share trading on electronic systems and, separately, the total trading volume, open interest and the rolling volatility measure discussed above. Scatterplots of these reactions are shown in Fig. 3A–C. In these figures, the Epanechnikov kernel smoother is applied; it brings the set of noisy data points into a smooth, high-trace line reflecting a functional association between the pairs of the examined variables.

As shown in this set of scatterplots, a higher share of electronic trading is associated with a sharp increase in open interest (Fig. 3B) and an increase in total trading volume (Fig. 3A), as highlighted by the rising kernel fit functions. In contrast, there is no discernible relationship between the higher share of electronic trading and the price volatility index (Fig. 3C). In particular, sharp increases in open interest and in trading volume are detected once the share of electronic trading exceeds 70%, with an explosive impact on open interest once it exceeds 85%. This highlights significant liquidity increases brought forth by electronic trading, particularly at the advanced stages of transition from pit to electronic trading (Phases III and IV).

Table 2
10-year T-note Futures open interest and trading volumes.

Trading characteristics >>>	Pit trading only	Leap to electronic trading	Electronic dominant trading	Electronic dominant with limited pit
Dates of period >>>	3 May 1982–27 Aug 2000	28 Aug 2000–11 Sep 2003	12 Sep 2003–26 Nov 2007	27 Nov 2007–31 Dec 2011
Open interest	I	II	III	IV
Open interest during first 60 business days of the period (average of daily data, number of contracts)	17,381	559,267	991,186	3,988,858
Open interest during last 60 business days of the period (average of daily data, number of contracts)	599,417	989,853	3,393,939	2,987,847
Average open interest during the period, number of contracts	197,835	730,528	1,928,875	3,190,296
Standard deviation of daily open interest over the period, number of contracts	180,784	174,199	520,301	1,073,790
Coefficient of variation	0.91	0.24	0.27	0.34
Trading volume	I	II	III	IV
Trading volume during first 60 business days of the period (average of daily data, number of contracts)	6286	191,625	655,642	1,376,938
Trading volume during last 60 business days of the period (average of daily data, number of contracts)	155,076	658,037	1,370,109	1,015,198
Average trading volume during the period, number of contracts	55,489	357,967	940,297	1,075,025
Standard deviation of daily trading volume over the period, number of contracts	58,817	199,272	461,667	530,810
Coefficient of variation	1.06	0.56	0.49	0.49

Note: The notional value of one contract is US\$ 100,000 assuming a price of par or 100.
Data source: Futures volume and open interest data provided by the CME Group.

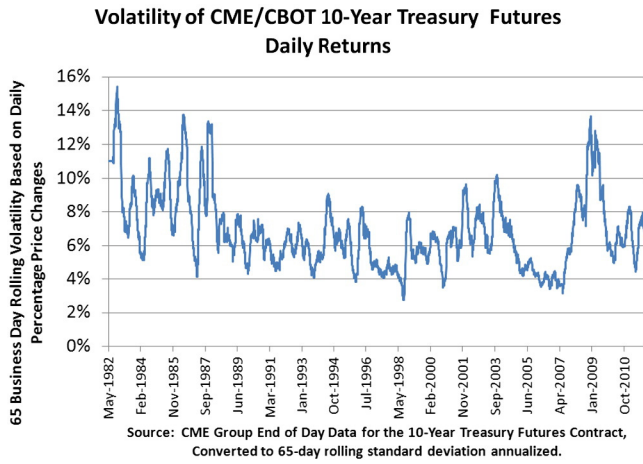


Fig. 2. Rolling volatility of 10-year T-note Futures daily returns.

A general conclusion from the above analysis is that the transition from pit to electronic trading has brought forth a considerable increase in liquidity in the 10-year T-note futures market, but not a discernible increase in volatility. I now proceed to a deeper investigation of volatility dynamics by employing GARCH(p,q) tests augmented with the generalized error distribution (GED) parameterization for each of the analyzed phases.

4. Impact on price volatility: GARCH-M-GED analysis

Price volatility of 10-year T-note futures is examined with the generalized autoregressive conditional GARCH(p,q) model augmented with the in-mean GARCH variance M and generalized error distribution GED parameterization. The in-mean variance allows for assessing the impact of a (one-period-lagged) conditional volatility on the volatility of returns, and the GED parameterization relaxes a rigid, normal (Gaussian) distribution assumption, reflecting the scope of leptokurtosis, i.e. long-tails in the examined series. The GARCH-M-GED process consists of a two-step procedure that includes the conditional mean and the conditional variance equations.

The conditional mean equation is specified as:

$$\Delta(PVT_t) = \gamma_0 + \gamma_1 \Delta(TVOL_t) + \gamma_2 \Delta \log(\sigma_{t-1}^2) + \mu_t. \quad (1)$$

The corresponding conditional variance equation is stated as:

$$\sigma_t^2 = h_0 + h_1 \mu_{t-1}^2 + \dots + h_p \mu_{t-p}^2 + v_1 \sigma_{t-1}^2 + \dots + v_q \sigma_{t-q}^2. \quad (2)$$

The price volatility series PVT_t is a regressant, and the daily average trading volume $TVOL_t$ as well as the lagged squared GARCH conditional variance term $\log \sigma_{t-1}^2$ are regressors in the conditional mean Eq. (1). The PVT_t series is constructed as the square root from the squared daily difference in the CME excess returns index $ERIND_t$ for 10-year T-note futures. Therefore, PVT_t is calculated as:

$$PVT_t = \sqrt{(ERIND_t - ERIND_{t-1})^2}. \quad (3)$$

In the conditional variance Eq. (2) innovations or shocks to volatility are represented by p-order ARCH terms $h_p \mu_{t-p}^2$ and the persistency in volatility is reflected by q-order GARCH terms $v_q \sigma_{t-q}^2$.⁴ To account for leptokurtosis in the data, the model includes general error distribution (GED) parameterization. If the estimated GED parameter is less than 2

⁴ Applications of GARCH-class tests for measuring volatility of U.S. Treasury futures markets have been pioneered by Li and Engle (1998), who devised a forecast model of futures prices based on macroeconomic announcement variables.

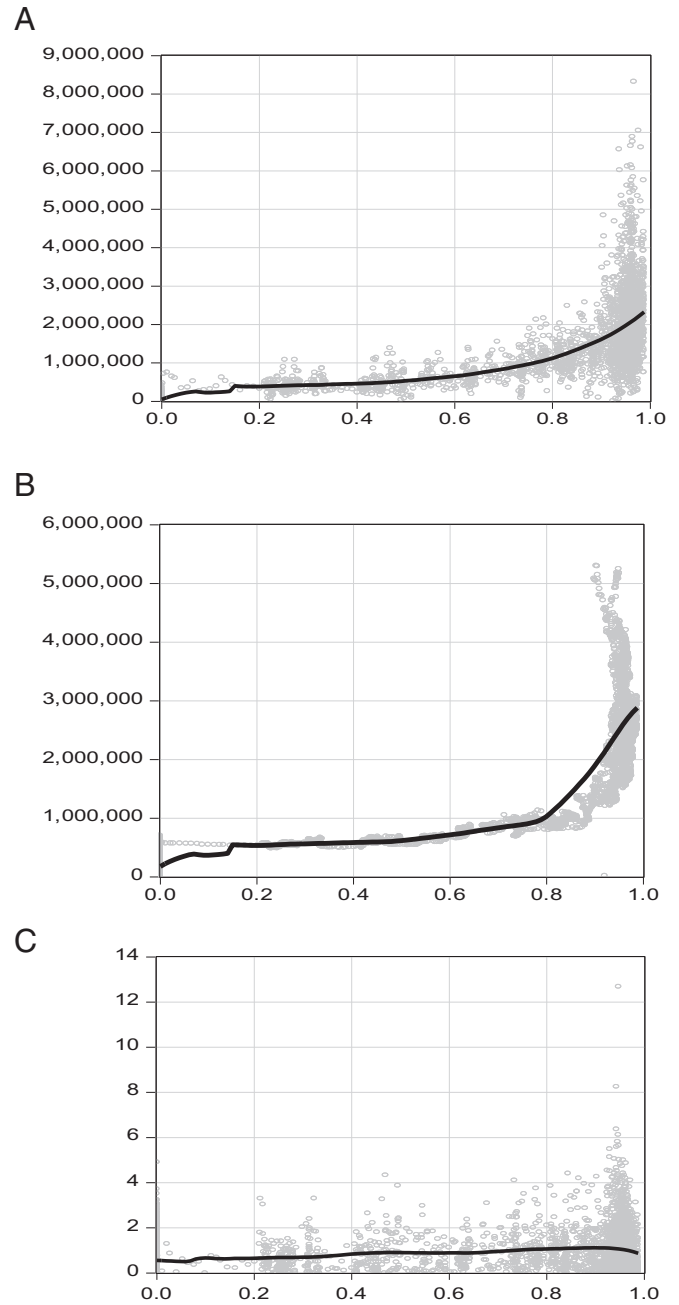


Fig. 3. A. Total trading volume of 10-year T-note Futures (left scale) in relation to percentage share of Globex Trading (Bottom Scale). Scatterplot with Kernel Fit (solid) Line. B: Open interest (left scale) in relation to percentage share of Globex Trading (Bottom Scale). Scatterplot with Kernel Fit (solid) Line. C: Price volatility index (left scale) in relation to the percentage share of Globex Trading (bottom scale). Scatterplot with Kernel Fit (solid) Line. Source: Author's own estimation based on CME Group data.

and closer to 0, the price volatility process has a leptokurtic “heavy-tailed” or “outlier-prone” distribution. The heavy-tailed distribution means that volatility of the examined data series is subdued (oscillating around the mean) at normal market periods, but it tends to explode at turbulent times, reflecting prevalence of extreme market risk. Outbursts of such risk have been recently quite pronounced during the recent global financial crisis. As demonstrated by Orlowski (2012), during the recent global financial crisis extreme market risks have been particularly predominant in interbank credit markets, while somewhat less endemic in equity and foreign exchange markets. Inclusion of the GED parameterization in the GARCH process is justified by the ubiquitous character of tail risks in financial markets. Moreover, such extreme market risks

have remained uplifted by ultra-easy monetary policies pursued by the Federal Reserve and other central banks (Putnam, 2013; White, 2012).

In addition, the model is aimed at examining whether an increase in conditional volatility, i.e. in a one-period lagged conditional variance, is associated with lower or higher price volatility. To capture this effect, the model includes the (log) of the GARCH variance (the M component) in the conditional mean equation. In essence, a negative sign of the GARCH variance coefficient implies price volatility compression in the presence of increasing conditional volatility of the examined series.

The empirical tests of the model specified by Eqs. (1) and (2) are shown in Table 3. The tests are conducted for each one of the four phases and separately for the entire sample period of May 3, 1982–December 31, 2011. As noted above, the empirical tests are based on a set of daily data. All the tests involve stationary dependent and independent variables. The ARCH and GARCH orders for each of the tests are optimized by minimizing the Schwartz Information Criterion. All variables are entered in their first-differences in order to ensure their stationarity.

The GARCH conditional mean equation estimation generates several meaningful results. Throughout the entire sample period and during each of the four examined phases, higher trading volumes are associated with rising price volatility, as implied by the positive values of the estimated γ_1 coefficients. This shows that higher trading volumes tend to drive up price volatility. This positive relationship is understandable, as investors normally use Treasury bonds and futures for the purpose of reducing volatility of their portfolios and increasing predictability of cash flows. Thus higher volatility induces investors to buy these securities, which in turn drives up their prices. Notably, this positive functional relationship is the most significant in the pit-only Phase I. It is still pronounced in Phases II and III, while in Phase IV this link is the weakest and statistically insignificant. The estimated in-mean GARCH variance coefficients are consistently negative and statistically significant in all four phases, indicating that elevated volatility in the previous day tends to decrease the price volatility in the following day. This observation may be related to the “risk-on, risk-off” nature of trading environments in the Treasury futures market, not really attributable to electronic trading.

The conditional variance equation provides a number of insights on specific features of volatility. Especially interesting is the changing pattern of unexpected shocks to volatility reflected by the lagged ARCH terms. First-order ARCH(1) shocks to volatility are highly significant in all four phases. Moreover, positive coefficients of ARCH(1) and negative coefficients of ARCH(3) terms have roughly the same absolute values, which suggests a two-day nearly complete diffusion of positive shocks. This effect seems to be prevalent during more turbulent market periods,

as it is relatively less significant in a more tranquil Phase III. In addition, the diffusion seems to be a bit more rapid in Phase III than in Phases I and II, as inferred by the significant, negative ARCH(2) term. This confirms what many researchers thought would happen in the electronic era – namely, that the impact of a given event or shock to markets is dispersed more immediately, as information flows faster to traders. Moreover, the conditional volatility is highly persistent, as implied by the GARCH(1) coefficients that are all close to the unity, with a notable exception of the most recent Phase IV. The weaker persistency in volatility during the recent period seems to be attributed to the market turbulence and elevated risks during the global financial crisis.

A particularly worth noting finding is that the estimated GED parameter for the pit-only phase is much lower than that for the remaining phases. This suggests that tail risks in the price volatility series were much stronger in the floor trading era than in the electronic era. This finding dismisses the early fears of many traders that the introduction of Globex would entail increasing volatility and extreme market risks in the Treasury futures markets (Melamed, 2009). Nevertheless, the GED parameter is lower in Phase IV than in Phase III. Thus in the period affected by the crisis induced financial shocks, the volatility series distribution became more leptokurtic, with fatter tails in both directions. Arguably, trading of 10-year T-note futures tends to be increasingly volatile at turbulent market (i.e. financial distress) periods as investors exercise flight-to-quality, while volatility remains subdued at more tranquil times.

The price volatility patterns are further highlighted by the GARCH conditional variance generated from the entire sample period estimation, which is shown in Fig. 4. The conditional volatility was very pronounced at the early stage of the pit-only Phase I (1982–1987). The volatility was considerably lower during the following 13-year period, although there were several noticeable “jumps” indicating high susceptibility to tail risks. It should be emphasized that the GARCH conditional variance series has not changed in Phase II, i.e. the leap to electronic trading, relative to Phase I. Notably, the examined volatility was clearly the lowest during the Globex-dominant Phase III. As it could be expected, the volatility was considerably elevated in Phase IV, with large increases at the peak of the financial crisis in September/October of 2008, and the largest single-day jump on March 18, 2009 coinciding with a sudden, unexpected increase in the price of 10-year Treasury note. Toward the end of Phase IV, in post-crisis period, the examined volatility has resumed its average historical pattern.

In sum, price volatility of 10-year Treasury note futures has been continuously associated with higher trading volumes during transition from pit to electronic trading. In the course of this transition, the

Table 3
GARCH(p,q)-M-GED tests (Eqs. (1) and (2)). Dependent variable: Daily change in price volatility of 10-year T-note futures $\Delta(PVT_t)$. Sample period: May 3, 1982–December 31, 2011.

Variables:	Phase I	Phase II	Phase III	Phase IV	Entire period
<i>Cond. mean equation:</i>					
Constant term	−0.0088*** (−7.37)	−0.0163*** (−3.78)	−0.0073*** (−2.97)	−0.0087** (−2.49)	−0.0070*** (−7.94)
$\Delta \log(TVOL_t)$	0.00076*** (7.58)	0.00076** (2.05)	0.00083*** (3.72)	0.00026 (0.71)	0.00076*** (8.78)
Log GARCH	−0.00078*** (−7.31)	−0.00147*** (−3.76)	−0.00062*** (−2.94)	−0.00081** (−2.47)	−0.00062*** (−7.88)
<i>Cond. variance equation:</i>					
Const.	0.000**	0.000	0.000	0.000*	0.000***
ARCH(1)	0.241***	0.206***	0.294***	0.144***	0.229***
ARCH(2)	0.002	0.089	−0.165	0.112	0.008
ARCH(3)	−0.201***	−0.240***	−0.110***	−0.245***	0.199***
ARCH(4)	NA	NA	NA	0.081**	NA
GARCH(1)	0.951***	0.907***	0.978***	0.876***	0.957***
GED parameter	1.467***	1.616***	1.637***	1.545***	1.495***
<i>Diagnostic statistics:</i>					
SIC	−8.084	−7.984	−8.620	−7.643	−8.106
Sum sq. resid.	0.102	0.016	0.012	0.032	0.162
Log likelihood	18,696	3064	4522	3982	30,238
#observations	4616	760	1042	1033	7451

Notes: Z-statistics are in parentheses; SIC = Schwartz Information Criterion; *** indicates significance at 1%, ** at 5%, * at 10%; NA = not applied due to sub-optimally high ARCH order. Source: Author's own estimation based on CME data.

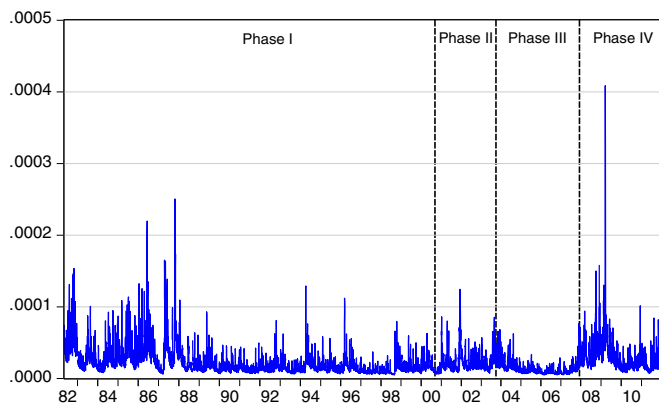


Fig. 4. GARCH conditional variance. Note: The GARCH conditional variance series is generated from estimation of Eqs. (1) and (2) for the entire sample period. Estimation representation is shown in Table 3, the right-hand side column. Source: Author's own estimation based on CME Group data.

conditional volatility pattern shows a faster diffusion of ARCH-type shocks and a somewhat weaker persistency. In Phase IV volatility is subject to more pronounced extreme risks, although this effect results very likely from a significant risk proliferation in all financial markets during the recent financial crisis.

5. A synthesis

The transition from pit to electronic trading was quite rapid, taking just less than three years for electronic trading to establish clear dominance. The key argument of our study is that the move to electronic trading of 10-year Treasury note futures was accompanied by substantial increases in both the trading volume and the levels of open interest, but not in price volatility. This effect is shown in Fig. 3A–C. It is further proven by the GARCH empirical tests of Eqs. (1) and (2), and by the GARCH conditional variance series shown in Fig. 4. The increases in trading volume and open interest can be attributed to: (1) the increased globalization of the market with near 24 h trading in the electronic era, as well as to the (2) joint impact of the lightning speed of trade matching engines coupled with lower transactions costs, allowing for more rapid or high frequency trading.

Across all analyzed periods, the days with higher trading volumes are associated with higher price volatility. That is, external shocks or surprises that hit the Treasury futures market simultaneously generate a greater propensity for price jumps (discontinuities) at the same time as trading volumes spike higher. Moreover, the obtained positive relationship between price volatility and trading volume is plausible since investors normally use Treasury bonds and bond futures for the purpose of reducing volatility of their portfolios and increasing predictability of cash flows.

The relationship between trading volumes and price volatility changed with transition to electronic trading. Volatility was the lowest during the Globex-dominant Phase III. This reflects a faster growth in trading volumes than in open interest and it can be generally interpreted as another manifestation of the greater liquidity and lower transaction costs available in the electronic era.

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